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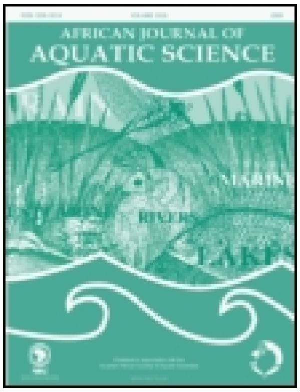

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Technical efficiency of small-scale fishing households in Tanzanian coastal villages: an empirical analysis

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The effort to conserve fisheries resources and improve the welfare of small-scale fishing households is an important objective of poverty reduction strategies in Tanzania. The success of such strategies depends on both the diversity and the level of efficiency within small-scale fishing households. This paper examines the technical efficiency of Tanzanian small-scale fishing households, based on data from two coastal villages located near Bagamoyo and Zanzibar, using a stochastic frontier model with technical inefficiency. The estimated mean technical efficiency of small-scale fishing households was 52%, showing that they were operating far below optimum efficiency. The efficiency of individual fishing households was positively associated with fishing experience, size of farming land, distance to the fishing ground and potential market integration; it was negatively related to non-farm employment and bigger household sizes. Future policies aimed at conservation and development in fishing communities should provide mechanisms that improve the access of small-scale fishing households to less-destructive fishing tools (via the provision of credit facilities) and to markets, as well as the creation of new employment opportunities in other sectors. In addition, measures which check the use of illegal fishing gear, overcapitalisation and open-access problems should be considered.

Keywords: coastal areas, fisheries development, policy development, socio-economic factors, stochastic production frontier

Introduction

Fisheries resources represent natural capital and are a potential source of sustainable wealth for many coastal communities in developing countries such as Tanzania. This wealth provides the opportunity for such resources to make an ongoing contribution to economic growth and poverty reduction. The problem is how to identify the policies which optimise this contribution. This paper investigates the pattern of technical efficiency in small-scale fishing households and how socioeconomic factors influence this pattern. This knowledge can be valuable in designing policies to improve overall efficiency and hence to improve the welfare of fishing households. This is vital, considering that the demand for fish in Tanzania is increasing due to population growth (particularly along the coast) and to the expansion of tourism (Francis and Bryceson 2001, TCMP 2003). For example, recent estimates show that the local annual per capita consumption of fish is 25–30kg per person (Jiddawi 2001).

In recent years, Tanzania has witnessed a poor performance of fisheries productivity in terms of production per unit effort. This is exacerbated by the lack of technical skills and capital to fish beyond the inshore waters, unregulated access (causing crowding of fishermen in coastal inshore waters) and the increased intensity of fishing in the coastal waters leading to over-fishing (Bagachwa and Maliyamkono 1994, Jiddawi 2001). Due to the lack of alternative employment opportunities, the increasing number of households that depend on fishing as their main source of livelihood has exacerbated the over-exploitation of fish stocks and the decline in fish catches. With the scarcity of resources and growing fish demand, decision makers, including policy makers and households, face the challenge of developing a sustainable small-scale fisheries sector that can incorporate socioeconomic and environmental objectives in their planning decisions.

To maintain even the current level of small-scale fishing production and environmental protection, greater effort should be made to enhance the efficiency of fisheries resource use. Increasing small-scale fishing households' productivity becomes a vital issue. Although the importance of linking fishing households' behaviour and their productivity has often been raised in policy debates on coastal resources management (Gaertner *et al.* 1999, Salas 2000, Salas and Gaertner 2004), there have not been any recent empirical studies done in Tanzania. This paper aims at identifying factors which influence the technical efficiency of small-scale fishing households in order to derive policy options for sustainable management of the small-scale fishery sector. It analyses the nature of small-scale fishing households' operations and their responses to regulations or other factors that influence participation in the sustainable management and utilisation of marine fisheries resources, and derives recommendations for developing efficient policies targetting marine and coastal resources conservation and household welfare.

Methods

A stochastic production frontier model was applied to household data from an on-site survey conducted in January–March 2004 of a sample of 217 households from two coastal villages (JKS and RSJT unpublished data), in order to measure the relative technical efficiency of small-scale fishing households. Our aim was to shed light on the factors associated with efficiency differences, following the methods used by Sharma and Leung (1999), Squires *et al*. (2003) and Lokina (2005).

The stochastic frontier model and technical efficiency

A stochastic production frontier model estimates technical efficiency in the production of an output by firms (in this case, small-scale fishing households) (Battese and Coelli 1995). This function allows for a non-negative random component in the error term to generate a measure of technical inefficiency. The level of technical efficiency is the ratio of actual output to expected maximum output (which would lie on the frontier), given inputs and existing technology (Figure 1). The production frontier is represented on the graph (Figure 1) as the line between 'O' and 'V'. The firm produce at Point A is technically efficient while the firm produce at B is technically inefficient. The technical efficiency score for the technically efficient firm is 1, while the technical efficiency is q/q*. The stochastic production frontier allows for technical inefficiency, but it also acknowledges the fact that random shocks beyond the control of producers can affect output. It accounts for measurement errors and the influence of other factors such as weather conditions, diseases etc. on the value of output variables, together with the effects of unspecified input variables in the production function. The stochastic frontier approach is preferred for assessing efficiency in fishing because of the inherent stochasticity involved (Kirkley *et al*. 1995).

However, the distribution to be used for the inefficiency error has been a source of contention (Griffin and Steel 2004). Since households in developing countries typically fall below the maximum that is possible, the deviation from actual maximum output becomes the measure of inefficiency and is the focus of interest for most empirical work. Increasing the technical efficiency would result in the growth of production without increasing costs. This effect may have some implications for poverty alleviation strategies. At the same time, pressure on the environment would be checked. In addition, as poor communities become more efficient at fishing, due to increased productivity, income distribution will also be improved. Increasing technical efficiency thus supports the three pillars of sustainability: (1) ecological soundness, i.e. the preservation and improvement of fisheries resources through use on non-destructive fishing gear and access to offshore fishing grounds; (2) economic performance, i.e. productivity improvement that leads to an increase in income; and (3) society, i.e. self-reliance and improved quality of life (i.e. poverty alleviation).

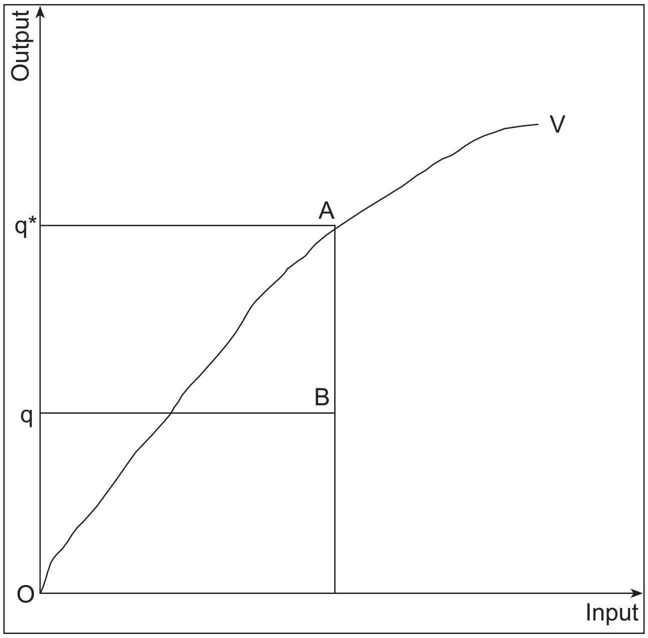

Figure 1: Technical efficiency and inefficiency

The model used for this study was an application of that proposed by Aigner *et al*. (1977) and extended by Huang and Liu (1994) and Battese and Coelli (1995) (see Appendix 1 for details).

Data and variables

The data used for this empirical application were a subsample of a random sample survey conducted in January–March 2004 on 217 households in Nyamanzi (western district) and Mlingotini village (Bagamoyo district) on the Tanzanian coast. These villages were purposely selected, after consultation with the Institute of Marine Sciences, Zanzibar, as being households that reflect the diversity of environmental conditions and economic opportunities available to households in the coastal area.

The experimental design and data collection were carried out, under supervision by the corresponding author, by trained enumerators who had experience with the villages surveyed. Information from households was gathered through questionnaires and observations. Structured interviews were conducted with heads of households, covering information on each household's demographic structure, labour allocation, land ownership, income sources, sales of outputs, access to markets, coastal resources problems and attitude towards the management of coastal resources. Household income from agriculture, fishing, seaweed farming, wage-paying employment and self-employment was estimated according to reported production (for consumption or sale) at prevailing market prices. Equipment associated with fishing and transport as well as other assets were valued subjectively by respondents, at current resale value. Of the 217 house-

Table 1: Selected characteristics of households participating in fishing. Active participation = 1, non-participation = 0

Variable	Variable code	Mean	Standard deviation
Total fish output (US$)	*totfish*	411.68	574.26
Yield (total output/hour) (US$)	*tfy*	0.67	0.75
Capital equipment value (US$)	*capital*	153.84	210.67
Fishing gear value (US$)	*gear*	43.84	56.55
Household size (persons)	*hhsize*	4.7	2.2
Experience in fishing (years)	*expf*	17.8	12.9
Land area owned (ha)	*land*	3.8	2.9
Distance to fishing ground (km)	*distf*	6.8	3.2
Non-farm income (US$)	*othy*	1 220.46	1 369.10
Transport cost (US$)	*tranpcost*	104.67	102.17
Participation* (%)	*partic*	74.2	–

holds surveyed, 124 participated in fishing, which was the predominant occupation in the study area. Sesabo and Tol (submitted) analysed other aspects of this data set.

Production frontiers in fisheries are generally depicted as a function of fishing effort and stock abundance (Cunningham and Whitmarsh 1980, Hannesson 1983). In theory, fishing effort includes all physical inputs used in harvesting (Anderson 1986) and in empirical works is typically represented as a function of certain easily-measurable production inputs. In the present study, these were fishing boats and gear.

Selected characteristics of households participating in fishing are set out in Table 1. The output of their fishing activity is presented in terms of total fishing income earned by the household, taking into account the US$ value of fish sold and consumed (during the survey 1 US$ was equivalent to 1 100 Tshs), while yield is measured as total fishing income (US$) produced per hour. The species are typically harvested in different seasons and are sold in different markets. We converted the measurements of catches (for example kilograms, buckets, baskets, number of fish etc.) to uniform prices across households. Therefore, the bulk of the variability in the dependent variable of the frontier model can be attributed to harvest rather than to price changes. Revenue has been used as an output measure in a number of Technical Efficiency studies (Neff *et al.* 1993, Coelli and Perelman 2000, Fousekis and Klonaris 2003). Due to the nature of fishing in the study area, access to the means of production — for example, the ownership of nets, canoes etc. — shapes the pathway by which households undertake fishing. In addition, the access to production-enabling resources, such as the renting of fishing boats, influences the productivity of fishing in most coastal communities. In fisheries, unequal access to inputs has consequences for fishing activities similar to those of unequal land ownership in agriculture. Access to fishing inputs is the main factor determining an individual household's share in the exploitation of fisheries resources and their benefit therefrom.

In the present study, boat ownership or rental, as well as the possession of fishing gear, are the main inputs used in fishing. Thus, boat ownership and the ability to rent were used as fishing inputs (a proxy for fishing capital), due to the fact that they require a large investment. The capital input was measured as the sum of the value of fishing boats and the rental cost. In addition to production inputs, fishing gear is used. All inputs are expressed in terms of their values in US$.

Variables representing household characteristics employed in the inefficiency analysis include agricultural land area, household size, household head's years of fishing experience, distance from shore to the fishing ground, access to markets (i.e. transport costs), and a 'dummy' variable representing participation in group activities.

The net effect of land ownership on fishing efficiency is ambivalent, since participation in agricultural activities may restrict production and decisions regarding fishing activities, thereby increasing inefficiency. On the other hand, an agricultural income might reduce the financial constraint, particularly for resource-poor small-scale fishing households, and could enable them to invest in fishing inputs. The assumption was that the household head, whether male or female, was also a primary decision maker for a household's participation in various activities.

A household's size also has an ambivalent effect. Family size is associated with the availability of labour time, and thus larger families are likely to be more efficient. On the other hand, a large household with more females and dependants is less efficient in fishing, due to its lack of fishing labour because, in coastal rural areas, fishing is a male-dominated activity. The fishing experience of the household head, which represents human capital, is generally postulated to have a positive impact on efficiency (Kurien 1990), since it enables heads of households to have information on fishing grounds, fish spawning areas and water currents. The distance from shore to the fishing ground used represents the availability of the fish stock and of fishing inputs. It is postulated that the greater the distance travelled to fishing grounds, the higher the household's fishing efficiency. In addition, distance travelled shows the capacity of small-scale fishing households to access offshore fishing grounds through their ownership of better fishing boats. Hence, the effect on technical efficiency is expected to be positive. Most fisheries resources near the shore are overexploited, due to the use of poor and destructive fishing methods, driven by an increase in population in coastal areas. Furthermore, low productivity and long travel times demotivate the operators.

Affiliation to fishing cooperative activities provides mechanisms for mutual aid among members. These associations and groups are established to secure labour, skills and credit. Therefore, the current study assumes that access to group activities has a positive effect on technical efficiency.

The net effect of off-farm employment on inefficiency was unclear, since participation in non-farm employment may restrict production in the fishing sector and thereby increase inefficiency. This may be due to the fact that, in rural coastal settings, most of these activities do not require a high level of initial capital and both fishing and off-farm employment activities are labour-intensive. Hence, participation in one activity reduces labour input into other activities. The impact of access to off-farm employment can have a similar effect on technical efficiency to that of the ownership of agricultural land.

In this study, transport costs were used to represent the relationship between market integration and technical efficiency. Those households incurring higher costs sell their products far from the villages and they integrate into markets outside the local village. This implies that households with the capacity to integrate into different markets by covering transport costs may be more efficient than those that cannot cover these costs.

Empirical model

Several functional forms have been developed to measure the physical relationship between inputs and outputs. The most common forms are the Cobb-Douglas (CD) and the transcendental logarithmic (translog) functions. The translog production function reduces to the CD if all the coefficients associated with the second order and the interaction terms of fishing inputs are zero. In this study, the generalised likelihood ratio tests were used to help to confirm the functional form and specification of the estimated models. The correct critical values of the test statistic come from an χ^2 distribution (at the 5% level of significance) and a mixed χ^2 distribution, which is drawn from Kodde and Palm (1986). This study employed the following translog stochastic production function:

$$\ln Y_i = \beta_0 + \beta_1 \ln capital + \beta_2 \ln gear + \beta_{11}(\ln capital)^2 + \beta_{22}(\ln gear)^2 + \beta_{12} \ln gear \ln capital + v\mathrm{u}_i - \mathrm{mu}_i \quad (1)$$

where the subscript i indicates the ith household in the sample (i = 1, 2, …., 124); ln represents the natural logarithm (i.e. logarithm to base e); $\beta_{ij} = 0$ for all $i \le j = 1$ implying that the type of production function is Cobb-Douglas. Symmetry has also been imposed by $\beta_{ij} = \beta_{ji}$ and the inputs are capital and fishing gear. Y represents the output of fish (i.e. the aggregate value of fish caught per day weighted by the respective prices); *capital* represents the value (in US$) of boat/s owned, shared or rented; *gear* represents the value of fishing gear (in Tshs); β_s are unknown parameters to be estimated, νu_i is a random stochastic disturbance term and $m\mu_i$ stands for technical inefficiency term.

In this study, the following model was used to estimate determinants of household-specific technical efficiency. The model is specified as:

$$\mathrm{mu}_i = \delta_0 + \delta_1 \ln(hhsize) + \delta_2 \ln(\exp f) + \delta_3 \ln(land) + \delta_4 \ln(distf) + \delta_5 \ln(otherinc) + \delta_6 \ln(tranpcst) + \delta_7 partic \quad (2)$$

where *hhsize* represents number of household members; *expf* represents household head fishing experience (in years); *distf* represents distance (km) to fishing ground; *land* represents the area (ha) of agricultural land owned; *otherinc* accounts for the availability of income (in US$) from other activities; *tranpcst* represents the total transport costs (in US$); *partic* represents the group dummy which has the value of 1 for households participating in groups, and 0 otherwise; δ_0 is the intercept and δ_i are unknown parameters to be estimated.

The parameters of the stochastic production frontier model Equation (1) and those for the efficiency model, Equation (2), were estimated simultaneously, using the maximum-likelihood estimation (MLE) program FRONTIER 4.1 (Coelli 1996).

The technical inefficiencies Equation (2) can only be estimated if the technical inefficiency effects, mu_i, are stochastic and have particular distribution properties (Coelli and Battese 1996). Therefore, the following null hypotheses were of interest and were tested: no technical efficiency; $\gamma = \delta_1 = \ldots\ldots = \delta_7 = 0$; technical efficiency effects are non-stochastic, $\gamma = 0$; and the household-specific factors do not influence the technical inefficiencies, $\delta_1 = \ldots\ldots = \delta_7 = 0$. Under $\gamma = 0$, the stochastic frontier model reduces to a traditional average response function that is without technical inefficiency. Various tests of null hypotheses for parameters in the frontier production functions as well as in the inefficiency model are performed using a generalised likelihood-ratio test statistic defined by:

$$\lambda = -2\left[\ln\{L(H_0)\} - \ln\{L(H_1)\}\right] \quad (3)$$

where $L(H_0)$ and $L(H_1)$ represent the value of the likelihood function under the null H_0 and the alternative H_1 hypotheses, respectively. If the null hypothesis is true, the remaining statistic has approximately a chi-squared or a mixed chi-squared distribution with the degree of freedom equal to the difference between parameters involved in the null and alternative hypotheses.

Since the coefficients of the translog stochastic frontier in Equation 1 do not have a straightforward interpretation, the elasticity of output with respect to k[th] (from Equation 1) inputs variable η_k, evaluated at mean values of the relevant data point, can be derived as:

$$\eta_k = \frac{\partial y}{\partial x_k} * \frac{x_k}{y} = \frac{\partial \ln y}{\partial \ln x_k} = \alpha_k + \sum \beta_{kj} \ln x_j \quad (4)$$

where *x's* are means of inputs variables (i.e. capital and gears) and y represents the total fishing output. The elasticity, η_k, measures the responsiveness of output to 1% change in k[th] (Equation 4) input. The measure of return to scale (RTS) represents the percentage change in output due to a proportional change in the use of all inputs. This is estimated as the sum of output elasticities for all inputs. If this estimate is greater than, equal to, or less than 1, one has increasing, constant or decreasing returns to scale, respectively.

Results

Descriptive statistics

Table 1 provides descriptive statistics of the selected characteristics of households participating in fishing. The 'yield gap' between the average and the lowest fishing yield was 0.61 US$/hr, and that between the average and the highest was 3.05 US$/hr. This suggests that there is considerable room for improving average fishing yield in the study area, given the available resources. The average values of capital equipment and gear were 153.84 US$ and 43.84 US$, respectively.

The small-scale fishing households had about 3.8ha of farm land, on average. A typical household consisted of 4.7 members, and the proportions of female workers and dependants within the surveyed sample were 31.12% and 33.12%, respectively. The household members participating in fishing had 17.8 years of fishing experience. On average, the distance travelled by household members to their fishing grounds was 6.8km.

A total of 74% of households had a member who participated in group activities. The average yearly income from other activities (such as self-employment or wage-paying employment) was about 1 220.46 US$. Fishing households had average transport costs of 104.70 US$ per year. The data show that the average fishing output of those households which had access to outside markets was higher than for those without such access. The average fishing output for small-scale fishing households with market access is US$ 482.46, whereas for those without access, the figure is US$ 273.51. This difference was statistically significant at 5% level (t = 1.93, p = 0.05). The data show that outside markets were more lucrative than local markets.

Several generalised likelihood-ratio tests regarding the stochastic frontier coefficients, inefficiency model and variance parameters are summarised in Table 2. The stochastic production frontier model results and efficiency model are presented in Table 3 and Table 4.

Production frontier

In order to be able to estimate the potential contribution of physical inputs to the level of fishing output, we estimated the normal production function using ordinary least squares. A total of 85% (Adj R^2 = 0.85) of the fishing output variation was explained by fishing capital and fishing gear (Table 3).

Considering that the Cobb-Douglas form is nested within the translog function form, the test is performed to determine whether the Cobb-Douglas or the translog specification is an adequate representation of the frontier production function. Table 2 shows that the null hypothesis of the Cobb-Douglas frontier form can be rejected by the data at a 5% critical level and, hence, all results presented in this study refer solely to translog.

The direct estimates of Equation (1) did not have any economic meaning. The production elasticities for the estimation of the translog model were evaluated by means of relevant data points defined by Equation (8) and were

Table 2: Hypotheses tests

Null hypothesis	Test statistics[a]	Critical value[b]	Decision
H_0: $\beta_{ij} = 0$ for all $i \le j$ = 1, 2, 3 (Cobb-Douglas Frontier)	12.76	7.81	Reject H_0
H_0: $\gamma = \delta_1 = ... = \delta_1 = 0$[c] (Fishing households are technically efficient — no inefficient effects)	585.2	17.75	Reject H_0
H_0: $\delta_1 = ... = \delta_7 = 0$[c] (Coefficients of the explanatory variables in inefficiency model are equal to zero)	582.6	16.81	Reject H_0
H_0: $u = 0$	2.1	3.84	Accept H_0

a : $\lambda = -2[\ln\{L(H_0)\} - \ln\{L(H_1)\}]$ has a χ^2 distribution
b: critical value is at 5% level
c: λ follows a mixed χ^2 distribution. The critical values are given by Kodde and Palm (1986)

Table 3: Parameter estimates of the Stochastic Production Frontier; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively

Variable	Production function		Stochastic Production Frontier	
	Coefficient	t-statistics	Coefficient	t-statistics
(Constant)	4.5483	1.61*	–3.5598	–11.6***
Ln (capital)	–1.5742	–2.84***	0.4297	6.1***
Ln (gear)	0.891	1.78*	0.4046	6.7***
Ln (capital)*ln (capital)	0.1423	3.61***	0.0068	1.4
Ln (gear)*ln (gear)	0.0291	0.74	–0.0013	–0.32
Ln (capital)*ln (gear)	–0.1078	–1.7*	–0.0059	–0.92
Variance parameters				
Sigma-squared ($\sigma^2 = \sigma^2 + \sigma v^2$)			0.0016	8.06***
Gamma [$\gamma = (\sigma^2/(\sigma^2 + \sigma v^2)$]			0.51	8.45***
Log likelihood			234.9	
Mean efficiency			0.52	
Observations			124	
Adjusted R^2	0.85			

Table 4: Summary of technical efficiency by households' characteristics

Household characteristics		Technical efficiency Mean	Standard deviation	n
Agricultural land ownership (ha)	0	27.15	0.0786	20
	0.1–2.5 hectares	44.69	0.1439	23
	2.6–5.5	50.86	0.1122	44
	Above 5.5	70.27	0.1822	37
Household size	Less than 3 members	55.23	0.2334	17
	3–5 members	51.66	0.2063	68
	Above 5 members	50.17	0.1742	39
Experience in fishing	Less than 5 years	21.9	0.0412	10
	5–10 years	37.38	0.0423	31
	Above 10 years	63.22	0.1594	77
Distance to fishing ground	Less that 5km	33.66	0.0798	51
	5–10km	59.42	0.1041	63
	Above 10km	94.8	0.0524	10
Other non-farm income	Less than 273 US$	23.28	0.0412	14
	273.5–545 US$	36.62	0.0462	32
	545.5–819 US$	46.23	0.0201	17
	Above 819 US$	67.62	0.1504	61
Group affiliation	Participants	55.79	0.1959	92
	Non-participants	39.87	0.1617	32
Total transport cost	Less than 91 US$	41.82	0.1365	78
	91.5–136 US$	59.41	0.144	17
	Above 136 US$	73.68	0.1769	29

0.45 (σ = 0.0207) and 0.32 (σ = 0.0416) for capital and fishing gear inputs, respectively. The standard errors of elasticities were computed using the formula proposed by Kalirajan and Tse (1989: 181). All the coefficients had a positive relationship with respect to output. If the capital value increases by 10%, there seems to be a possibility of increasing output by about 4%. The return to scale parameter was found to be 0.77 (σ = 0.0256), implying a decreasing return to scale (expansion of all inputs by 1% increases output by 0.77%). The standard error was calculated using the following formula: Var (return to scale) = Var (capital) + Var (gears) + 2cov (capital, gears), with the assumption that the covariance between two variables is approximately equal to zero. This is consistent with expectations, since the minimum efficiency scale amongst small-scale fishermen in developing countries is usually below 50%. This may be partly explained by the lack of communication and transport infrastructure, imperfect inputs and output markets, as well as poor fishing tools, due to poverty.

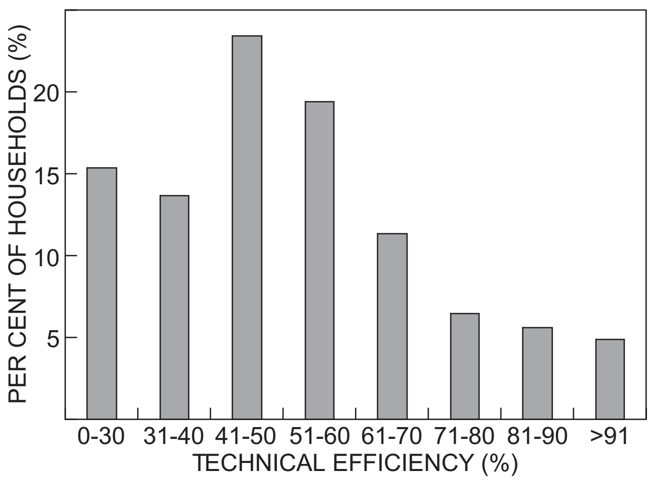

Figure 2: Distribution of Technical Efficiency score frequencies amongst the small-scale fishing households surveyed

Technical efficiency distribution and heterogeneity

Summary statistics of efficiency scores by household characteristics are given in Table 4. The results obtained suggest a significant degree of heterogeneity by small-scale fishing households and their characteristics. The average efficiency scores were higher for those small-scale fishing households with large agricultural lands, better access to far fishing grounds and markets, and other employment opportunities. This suggests that better access to these factors could improve efficiency.

Figure 2 provides frequency distributions of efficiency estimates using the efficiency estimates for all small-scale fishing households. A technical efficiency measure of 100% indicates complete efficiency of use of the inputs included in the frontier function specification. Figure 2 shows that the technical efficiency ranged from 13–100%, with mean technical efficiency estimated at 51.68%. This implies that, on average, small-scale fishing households could increase production by 48.12% by improving their technical efficiency. The results indicate that about 53% had a technical efficiency of less than or equal to 50%, about 20% had efficiency scores of 51–60%, about 10% had technical efficiency ranging from 61–70%, and only 17% had a technical efficiency above 70%. Despite this wide variation in efficiency, it is clear that about 70% of households had a technical efficiency level of less than 61%, implying that a considerable amount of additional production could be obtained by improving the technical efficiency of small-scale fishing households.

The null hypothesis is that small-scale fishing households are technically efficient, that inefficiency effects are absent and that the variables included in the inefficiency effect model have no effect on their level of technical efficiency. Since the joint effect of these variables on efficiency was statistically significant (Table 2), this hypothesis can be rejected. The estimated value of the γ-parameter, which is associated with the variance of the technical inefficiency effects in the stochastic frontier, was 0.51 (Table 3). This suggests that technical inefficiency effects are significant components of the total variability of fishing output for the sample of households (Battese and Coelli 1995). The null hypothesis that the explanatory variables in the technical inefficiency model are not stochastic is rejected by the data. Therefore, small-scale fishing households are not technically efficient. Thus, it can be concluded that the factors that affect technical efficiency in the technical efficiency model do contribute significantly to the explanation of the technical inefficiency effects for small-scale fishing households in the study area.

The last assumption to be tested was that the inefficiency factor error term mu_i had a truncated normal distribution, obtained by truncating (at zero) the normal distribution with mean, and variance σ^2_{mu}. If mu is pre-assigned to be zero, then the distribution is semi-normal. Table 2 shows that the null hypothesis cannot be rejected by the data, which indicates that the distribution of mu_i is semi-normal.

Determinants of technical inefficiency

To answer the question as to why some fishing households are more efficient than others, a negative sign on a parameter means that that variable improves technical efficiency, and vice versa. Table 5 lists coefficients of the explanatory variables of the technical inefficiency model. As expected, the coefficient of experience (*expf*) was negative, indicating that fishing experience is valuable. Participating household members with more years of experience in fishing are found to be more efficient than their less experienced counterparts. The fishing experience variable appears to be an important human capital for increasing fishing productivity. This result is consistent with earlier studies on fishing sectors (Sharma and Leung 1999, Squires *et al*. 2003, Lokina 2005, Tingley *et al*. 2005) (also see Appendix 2).

The coefficient of land area (*land*) is found to have a significant influence on technical inefficiency (Table 5) and households owning large tracts of land are more efficient than those with less land. The most likely reason for this is that, in coastal settings, landless fishermen lack the opportunity to increase their capital resources, which are essential in improving their fishing productivity. This suggests that agricultural land provides an important complement to fishing activities, because of the lack of institutional investment capital for the fishing activity. These results are consistent with the findings of Sesabo and Tol (unpublished data) for rural coastal households, who found that land endowment was often associated with higher fishing income and a higher investment in fishing. In addition, Bailey and Pomeroy (1996) showed that many artisanal fishermen in south-east Asia possess land, which enables them to combine fishing with farming.

Table 5: Estimated Technical Inefficiency Function; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively

Variable	Coefficient	t-statistics
(Constant)	4.4557	18.43***
Ln (*hhsize*)	0.3516	9.97***
Ln (*expf*)	–0.1346	5.79***
Ln (*land*)	–0.0078	5.19***
Ln (*distf*)	–0.0978	1.97**
Ln (*otherinc*)	0.0063	5.28***
Ln (*transpcost*)	–0.3358	9.84***
Partic	–0.0041	0.38

The distance to the fishing grounds (*distf)* has a parameter value of δ = –0.09 (Table 5), showing that fishermen who travel long distances to fishing grounds tend to be more efficient than their counterparts who fish closer to home. This is as expected, since a long distance to a fishing ground would imply the capacity to access fishing grounds which have larger fish stocks. The result indicates that those households that manage to access far-off fishing grounds normally catch more fish. This result is further supported by the fact that fishermen with high-value fishing boats travel longer distances because their boats are more advanced, compared to those of their counterparts. This result points toward the wealth issue, i.e. that richer households can afford stronger vessels and are capable of reaching further-offshore fishing grounds and sites. In contrast, poorer households may not be able to go beyond the inshore fishing grounds, which are highly degraded due to overexploitation. Nevertheless, distance (*distf*) and boat value were found to be only weakly correlated.

Concerning potential market integration (*tranpcost*), the coefficient indicates that households with higher transport costs tend to be more efficient (Table 5). Market integration involves transaction costs from markets, poor infrastructure, and high market margins (Sadoulet and de Janvry 1995). In Tanzanian coastal areas, as in other rural areas in developing countries, transaction costs emanate from a number of sources. Small-scale fishing households are located in remote areas far from service providers and major consumers of fishing products. The distance to market, when combined with poor infrastructure, a lack of assets, and poor access to information, is manifested in higher exchange costs. The results indicate the presence of transaction costs, which suggest that rich fishing households are able to integrate into markets that are unavailable to their poorer counterparts. This enables them to secure high prices. As a result, richer fishing households are able to increase their productivity and hence they tend to have a higher level of efficiency. In addition, households with higher transport costs have market security, due to the fact that they can sell their products in various markets, including both local and town markets. This is consistent with the findings of Halafo *et al*. (2004), who showed that infrastructure and lack of access to markets are constraints facing artisanal fishermen at Lake Malawi.

The coefficient for household size (*hhsize)* is significant and positively associated with technical inefficiency (Table 5). Thus, larger households tend to be less efficient than smaller ones. This is consistent with our prior results, which indicate that efficiency score decreases with increasing household size (see Table 4). The correlation between the proportion of dependants and female workers in a household and household size was found to be positive and significant at the 1% level (0.4042). The descriptive statistics indicate that, as total number of dependants and female workers increase, the technical efficiency score tends to decrease. For example, households with a total number of dependants and of female workers less than two have an average technical efficiency score of 54.56%, while those households with greater than three had a score of 49.36%. Parikh and Shah (1994) and Karki (2004) reported a positive relationship between household size and the technical inefficiency of small-scale farmers in Pakistan and Nepal, respectively. Consequently, an increase in household size means a reduction of labour force, as a result of the increased number of dependants. However, on the east coast of Malaysia, Squires *et al*. (2003) found that an increase in family size also increased their efficiency (see Appendix 2).

The income from other non-farming activities accruing to households (*otherinc*) has a significant positive impact on inefficiency. This result is in contrast to the descriptive statistics, which show a negative correlation between inefficiency and income from such employment. Thus, households with more income from these activities are more efficient than their counterparts. One possible explanation of this could be that landless small-scale fishing households have significantly (p = 0.0418) low-valued fishing capital, as compared to their rich counterparts, and that this disadvantages them in terms of fishing. As a result, they opt to allocate most of their labour into other employment opportunities, thus reducing the labour supply for fishing activities, which are essential for enhancing production efficiency. As a result, the supply of labour to off-farm activities by households could possibly be restricting fishing production and thereby lowering the level of technical efficiency.

Discussion

Studies of technical efficiency in fishing activity are crucial to the success of marine and coastal resources conservation initiatives as well as poverty-reduction strategies in coastal areas in developing countries. Understanding the underlying factors, which influence the level of technical efficiency of small-scale fishing households, is essential if sound advice is to be provided to policy makers dealing with the sustainable utilisation of fishery resources. According to our results, it seems that technical efficiency levels differ across small-scale fishing households. Estimated production efficiency, measured by the production efficiency index, ranged from 13% to about 99.9% with the average efficiency index being 52%. These results suggest that these small-scale fishing households could increase their technical efficiency and output through the better use of available resources, given the current state of technology.

However, affiliation to groups, in terms of sharing and renting fishing assets, does not appear to alter the extent to which fishing households are able to produce maximum output with a given mix of inputs. This suggests that efficiency-enhancing policies need not discriminate among households on the basis of whether or not they participate in communal activities.

From the perspective of sustainable fisheries utilisation, improved efficiency of small-scale fishing households is desirable; the findings above provide some policy implications for promoting efficiency in the two villages studied and in Tanzania in general. In particular, the positive effect of distance to fishing grounds indicates that increased access to productive fishing grounds will augment the productivity of small-scale fishing households, since they would then be able to access less heavily-fished fishing grounds. There is an indication that good-quality fishing boats play an important role in accessing fishing grounds. This empirical finding strongly suggests that measures should focus on fostering the introduction of improved fishing boats, due to the view that in developing countries most small-scale fishing households, have been unable to fully exploit the available fish resources (Anderson 1986, Friedman 1998). Moreover, Jiddawi and Öhman (2002) substantiate the findings that small-scale fishing households in Tanzania are characterised by the use of traditional simple low-cost vessels, although recently more modern technologies such as motorised boats have been introduced. Most of these vessels lack cooling and freezing facilities, so their fishing is limited by both time and distance. That is, small-scale fishing households continue to fish the same grounds that were fished by earlier generations. This has led to the problem of over-fishing, which in turn decreases fishing productivity (Sesabo and Tol 2005, Silva 2006). Thus, the adoption of policies that are geared towards the provision of investment in motorised fishing boats and fish storage facilities are essential, in order to improve fishing efficiency and to enable small-scale fishing households to access distant less-exploited areas with abundant fish resources. Because more profitable fishing gear and boats are expensive to purchase and operate, it follows that the promotion of improved credit facilities is essential. However, to ensure the sustainable utilisation of fisheries resources, this should be done carefully, so as to ensure that the additional costs are recovered through increased catches and improved fish quality.

Another important finding was the significant influence of market integration through transport costs on the efficiency of small-scale fishing households. The data suggest that small-scale fishing households that are able to cover high transport costs are more efficient than households that do not incur high transport costs. Thus, households with higher costs have more potential to integrate into different markets, while those without the capacity to integrate into different markets miss the opportunities for efficiency gains. From the perspective of a poor household, this indicates that the lack of market access creates disincentives for catching more fish. Indeed, poor infrastructure, which leads to high transport costs, has been identified as one of the major impediments to small-scale fishing households in coastal villages (Sesabo and Tol 2005). These results point to a need for improving market access (such as investing in infrastructure), especially for poorer households, so as to enhance efficiency.

Market integration indicates that transaction costs, especially those associated with the distance to and from the market, tend to decline when roads are improved. All things being equal, declining transaction costs increase the value of the output, and hence motivate small-scale fishing households to catch more fish. Kaimowitz and Angelsen (1998) observed that improved market access through road construction could lead to increased degradation of the natural resources (e.g. deforestation). This can also be the case in fisheries resources, due to the fact that a reduction of the transaction costs could lead to more households taking up fishing. In addition to infrastructure distribution, equal income distribution among small-scale fishing households is essential for the promotion of market entry for poor households. In general, policies geared towards infrastructure development and income distribution can also induce the overexploitation of fisheries resources by failing to take into account the opportunity cost of the possible loss of fisheries resources. Again, careful analysis of the environmental benefits and costs associated with these policies is required. To achieve this, further research is needed to identify those opportunities that would increase the efficiency of small-scale fishing households in the Tanzanian coastal communities, through the improvement of markets and income distribution, while ensuring sustainable use of the fish resources.

The level of fishing experience is positively correlated with the technical efficiency of small-scale fishing households. In most developing countries, fishing is an hereditary occupation. This has resulted in the accumulation of knowledge about the marine environment and its resources through a process best described as 'knowledge-through-labour' (Kurien 1990), and has produced a plethora of technologies for fish harvesting pertaining to specific seasons or species. This indicates the importance of considering the level of fishing experience when designing sustainable fisheries management policies.

The negative effect of household size on technical efficiency indicates the traditional division of labour in coastal villages, where fishing is dominated by adult males. Moreover, the significant negative effect of non-farm employment may be because the labour competition effect outweighs the income effect. In order to achieve sustainable fisheries management, this implies that helping people to increase their non-fishing assets could lead to less pressure on the fisheries resources and would be good for the coastal environment. Diversification, both inside and outside the fisheries sectors, will reduce the pressure on fish stocks, reduce small-scale fishing households' poverty and vulnerability, and reinforce the integration of fishing communities into local development.

Conclusions

There is a need for renewed and committed focus to address problems affecting small-scale fishing households. Evidence from the literature indicates that any conservation-development strategy that neglects a consistent consideration of small-scale fishing household characteristics is unlikely to succeed, given the inherent weakness of the social, economic and natural environment. The experience in Tanzania, as in many developing countries, is that achieving conservation-development objectives in the fishing sector is not possible in the absence of knowledge about small-scale households' characteristics. The understanding of the level of efficiency of small-scale fishing households is crucial for improving fishing yields, and consequently reducing widespread food insecurity as well as poverty, which ultimately threaten the sustainability of fisheries-based livelihoods.

Overall, the study indicates that substantial productivity gains can be obtained by continuously improving small-scale fishing households' production efficiency. Hence, it is important to have government policies that facilitate the access of households to improved fishing tools, markets and credit facilities. Although affiliation to group activities did not show a direct effect on efficiency, there is a need among international, governmental and non-governmental organisations to recognise the importance of the formation of viable groups, such as those sharing a boat or fishing gear, so as to channel their support to these kinds of groups. Formal recognition of these groups is worthwhile, due to their role in fishing activities (Anderson and Ngazy 1998). Nonetheless, these efforts to ensure sustainable fisheries management require the right mix of policies for a particular human environment. This implies that measures that check overcapitalisation, excessive fishing effort, and open access problems are essential, to achieve poverty reduction as well as fisheries resources conservation.

Despite our limited cross-sectional data, which make it impossible to estimate multi-seasonal and time-varying efficiency, this study sheds light on the sources of inefficiency faced by small-scale fishing households in Tanzanian coastal areas. To get a clearer picture of the causes of fishing inefficiency, seasonal and panel data are required. As in other developing countries, the data on fishing household behaviour in Tanzania are limited. In order to build up panel data concerning the behaviour of fishing households, there is a need for government, non-government organisations and research institutions to invest in more information-gathering. This is necessary so as to gain a wider knowledge of small-scale fishing household characteristics, which is crucial in the design of policies that deal with poverty reduction.

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References

Aigner DJ, Lovel CAK and Schmidt PJ (1977) Formulation and estimation of Stochastic Production Function Models. *Journal of Econometrics* **6**: 21–37.

Anderson LG (1986) *The Economics of Fisheries Management*. John Hopkins University Press, Baltimore, MD, pp 27–43.

Anderson J and Ngazy Z (1998) Coastal communities' production choices, risk diversification, and subsistence behavior: responses in periods of transition, case studies from Tanzania. *Ambio* **27**: 686–693.

Bagachwa MD and Maliyamkono TL (1994) *Fisheries and Development in Tanzania*. Macmillan Press, London, pp 10–13.

Bailey C and Pomeroy C (1996) Resource dependency and community stability in coastal fishing communities of southeast Asia. *Society and Natural Resources* **9**: 191–199.

Battese GE and Coelli TJ (1995) A model for technical inefficiency effects in a stochastic frontier function for panel data. *Empirical Economics* **20**: 325–332.

Battesse GE and Corra GS (1977) Estimation of a Production Frontier Model with Application to the Patoral Zone of Eastern Australia. *Australian Journal of Agricultural Economics* **21**: 169–179.

Battesse GE and Corra GS (1977) Estimation of a Production Frontier Model with Application to the Pastoral Zone of Eastern Australia. *Australian Journal of Agricultural Economics* **21**: 169-179.

Coelli TJ (1996) *A guide to FRONTIER Version 4.1: computer program for Frontier production function estimation*. CEPA Working Paper 96/07, Department of Econometrics, University of New England, Armidale.

Coelli TJ and Battese GE (1996) Identification of factors which influence the technical efficiency of Indian farmers. *Australian Journal of Agricultural Economics* **40**: 19–44.

Coelli TJ and Perelman S (2000) Technical efficiency of European railways: a distance function approach. *Applied Economics* **32**: 1967–1976.

Cunningham D and Whitmarsh D (1980) Fishing efforts and fishing policy. *Marine Policy* **5**: 309–316.

Fousekis D and Klonaris S (2003) Technical efficiency determinants for fisheries: a study of trammel netters in Greece. *Fisheries Research* **63**: 85–95.

Francis J and Bryceson I (2001) *Tanzanian coastal and marine resources: some examples illustrating questions of sustainable use*. Chapter 4. In: Ahmed J, Bergstrom C, Bryceson I, Child B and Francis J (eds) Lessons Learned — Case Studies in Sustainable Use. IUCN, Gland, Switzerland, pp 76–102.

Friedman A (1998) *World Fisheries: What is to be Done.* Baird Publications, Victoria, Australia.

Gaertner D, Pagavino M and Marcano J (1999) Influence of fisher's behavior on the catchability of surface tuna school in the Venezuelan purse-seine fishery in the Caribbean Sea. *Canadian Journal of Fisheries and Aquatic Science* **56**: 394–406.

Green WH (1990) A gamma-distributed Stochastic Frontier Model. *Journal of Econometrics* **46:** 141–164.

Griffin JE and Steel MFJ (2004) Semi-parametric Bayesian Inference for Stochastic Frontier Models. *Journal of Econometrics* **123**: 121–152.

Halafo JS, Hecky RE and Taylor WD (2004) The artisanal fishery of Metangula, Lake Malawi/Niassa, East Africa. *African Journal of Aquatic Science* **29**: 83–90.

Hannesson R (1983) Bioeconomic production functions in fisheries: theoretical and empirical analysis. *Canadian Journal of Fisheries and Aquatic Science* **40**: 968–992.

Huang C and Liu J (1994) Estimation of non-neutral stochastic frontier function. *Journal of Productivity Analysis* **5**: 171–180.

Jiddawi NS (2001) *Marine fisheries in Tanzania.* In: Ngusaru A (ed) Present State of Marine Science in Tanzania. Tanzania Coast Management Partnership working documents, pp 64–99.

Jiddawi NS and Öhman MC (2002) Marine fisheries in Tanzania. *Ambio* **31**: 518–527.

Kaimowitz D and Angelsen A (1998) *Economic models of tropical deforestation: a review*. Centre for International Forestry Research (CIFOR) report, CIFOR, Bogor, Indonesia.

Kalirajan KP and Tse YK (1989) Technical efficiency measures for the Malaysian food manufacturing industry. *The Developing Economies* **27**: 174–184.

Karki LB (2004) *Impact of Project Intervention on Rural Households in Nepal: Assessment of Socio-economic and Environmental Implications*. Unpublished PhD Thesis, University of Giessen, Germany.

Kirkley JE, Squires D and Strand IE (1995) Assessing technical efficiency of commercial fisheries: mid-Atlantic sea scallop fishery. *American Journal of Agricultural Economics* **77**: 686–697.

Kodde D and Palm F (1986) Wald criteria for jointly testing equality and inequality restrictions. *Econometrica* **54**: 1243–1248.

Kumbhakar S and Lovell KCA (2003) Stochastic Frontier Analysis. Cambridge University Press, UK.

Kurien J (1990) *Knowledge systems and fishery resources decline: a historical perspective*. In: Lenz W and Deacon M (eds) Ocean Sciences, their History and Relation to Man. DHZ Publications, Hamburg, Germany.

Lokina RB (2005) *Efficiency Risk and Regulation Compliance: Applications to Lake Victoria Fisheries in Tanzania*. PhD Thesis, Göteborg University, Sweden, pp 1–24.

Neff D, Garcia P and Nelson C (1993) Technical efficiency: a comparison of methods. *Journal of Agriculture Economics* **44**: 479–489.

Parikh A and Shah K (1994) Measurement of technical efficiency in North-West Frontier Province of Pakistan. *Journal of Agricultural Economics* **45**: 132–138.

Ritter C and Simar L (1997) Pitfalls of normal-gamma Stochastic Frontier Models. *Journal of Productivity Analysis* **8**: 167–182.

Sadoulet E and de Janvry A (1995) *Quantitative Development Policy Analysis*. Johns Hopkins University Press, Baltimore.

Salas S (2000) *Fishing Strategies of Small-scale Fishers and implications for Fisheries Management*. PhD thesis, Resource Management and Environmental Studies, The University of British Columbia, Vancouver, BC, pp 154

Salas S and Gaertner D (2004) The behavioral dynamics of fishers: management implications. *Fish and Fisheries* **5**: 153–167.

Salas S (2000) *Fishing Stategies of Small-scale Fishers and implications for Fisheries Management.* PhD thesis, Resource Management and Environmental Studies, The University of BritishColumbia, Vancouver, BC.

Sharma KR and Leung P (1999) Technical efficiency of long-line fishery in Hawaii: an application of a stochastic production frontier. *Marine Research Economics* **13**: 259–274.

Silva P (2006) *Exploring the linkage between poverty, marine-protected area management, and the use of destructive fishing gear in Tanzania.* World Bank Policy Research Working Paper WPS 3831. The World Bank, Washington DC.

Squires D, Grafton Q, Alam F and Omar IH (2003) Technical efficiency in the Malasyian gill-net artisanal fishery. *Journal of Environment and Development Economics* **8**: 481–504.

Tanzania Coast Management Partnership (TCMP) (2003) *Tanzania State of Coast Report: the National ICM Strategy and Prospects for Poverty Reduction*. TCMP Coastal Management Report, 2002. TCMP.

Tingley D, Pascoe S and Coglan L (2005) Factors affecting technical inefficiency in fisheries: stochastic production frontiers versus data envelopment analysis approaches. *Fisheries Research* **73**: 365–376.

Appendix 1

The stochastic production function is specified as follows:

$$\ln(y_i) = X_i\beta + \varepsilon_i \text{ where } \varepsilon_i = \nu_i - \mu_i \text{ (Stochastic Frontier Model)} \quad \text{(i)}$$

where i = 1, 2,......,N; *yi* measures the value of fishing output of the i^{th} household; X_i is (1 x K) vector of value of the inputs and other explanatory variables; and β is a 1 x K vector of unknown scalar parameters to be estimated. The error term ν_i is assumed to be independently and identically distributed as $(N(0, \sigma^2_\nu)$ and captures random variation in output due to factors beyond control of the households (e.g. weather). The error term μ_i is a non-negative random variable, accounting for the existence of technical inefficiency in production and it is identically distributed as half-normal $mu_i \sim |N(0, \sigma^2|$. Following Battese and Coelli (1995), the mu_i is specified as:

$$\mu_i = \delta_0 + z_i\delta + \omega_i \quad \text{(Inefficiency Model)} \quad \text{(ii)}$$

where ω_i is distributed following $(N(0, \sigma^2_\omega)$, z_i is a vector of household specific effects that determine technical inefficiency and δ is a vector of parameters to be estimated. Household specific factors that may affect technical efficiency include household size, fishing experience, and agricultural land-ownership, among others. Input variables may be included in both Equations (i) and (ii), provided that technical inefficiency effects are stochastic (Battese and Coelli 1995).

The condition that $\mu \geq 0$ in Equation (i) guarantees that all observations either lie on, or are beneath, the stochastic production frontier. Following Battese and Corra (1977) and Battese and Coelli (1995), the variance terms are parameterised by replacing σ^2_ν and σ^2_μ with $\sigma^2 = \sigma^2_\mu + \sigma^2_\nu$ and $\gamma = \sigma^2_\mu / \sigma^2_\nu + \sigma^2_\mu$. The technical efficiency of the i^{th} household can be defined as:

$$TE_i = \frac{E(y_i \,|\mu_i\,,\ x_i)}{E(y_i\,|\mu_i = 0, x_i)} = e^{-\mu_i} = \exp(-\delta_0 - z_i\delta - \omega_i) \quad \text{(iii)}$$

and clearly must have a value of between 0 and 1. The measure of technical efficiency is thus based on the conditional expectation *on*, given by Equation iii, given the value of $vu_i - mu_i$ evaluated at the maximum likelihood estimates of the parameter in the model, where the expected maximum value of Y_i is conditional on $mu_i = 0$ and the overall mean technical efficiency of households is:

$$TE = \left\{ \frac{1-\phi\left[\sigma_{\text{mu}} - (\text{mu}/\sigma_{\text{mu}})\right]}{1-\phi(\text{mu}/\sigma_{\text{mu}})} \right\} e^{-\text{mu}+(1/2)\sigma^2_{\text{mu}}} \quad \text{(iv)}$$

where $\phi(.)$ represents the density function for the standard normal variable.

A variety of distributions (e.g. exponential, truncated-normal and gamma) are used to characterise the technical efficiency term mu_i in the literature that apply the stochastic production frontier (see Kumbhakar and Lovell 2003 for a more comprehensive discussion of alternative distribution assumptions found in the literature). While models that involve two distribution parameters (e.g. gamma and truncated normal) can accommodate a wider range of possible distributional shape, their application appears to come at a potential cost of increased difficulty in identifying parameters (see Ritter and Simar 1997). Different simulation exercises carried out by Greene (1990) indicated that the most straightforward model (i.e. half normal) is more appropriate from an econometric point of view (for details, see Kumbhakar and Lovell 2003: 90–91). Hence our analysis of the factors affecting small-scale fishing households' efficiency is based on the half-normal model (see test in Table 2).

Appendix 2: Findings from other studies; * and ** indicate significance at the 1% and 5% levels, respectively

Study and variable	Coefficient
Fishing experience	
Sharma and Leung (1999)	–0.07*
Squires *et al.* (2003)	–0.03*
Tingley *et al.* (2005)	–3.61*
Lokina (2005)	–0.58**
Household size	
Squires *et al.* (2003)	–0.08**